



Parity-relation-based state-of-health monitoring of lead acid batteries for automotive applications

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ARTICLE INFO

Article history:

Received 26 October 2009

Accepted 31 May 2010

Available online 25 June 2010

Keywords:

Fault detection

Fault diagnosis

Failure detection

Automotive batteries

Power systems

ABSTRACT

Effective vehicular power management requires accurate knowledge of battery state, including state-of-charge (SOC) and state-of-health (SOH). This paper presents an integrated algorithm for reliable battery SOH monitoring. The dynamics of lead acid batteries during engine cranking is investigated, and a new battery model is presented. Moreover, a parity-relation-based integrated method for battery SOH monitoring is proposed. It is shown that the diagnostic residual combines the SOH information provided by both battery resistance and voltage loss during engine cranking, hence enhancing diagnostic performance. Extensive evaluation results using real vehicle cranking data have verified the effectiveness of the proposed method.

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1. Introduction

The number of electrical devices in modern vehicles has been rapidly increasing in the last two decades, and this trend will accelerate (Emadi, Ehsani, & Miller, 2004; Salman, Popp, Zhang, Zhang, & Chin, 2006). The automotive electric power generation and storage (EPGS) system is required to supply sufficient power not only to safety-related systems (for instance, anti-lock braking system and stability enhancement system), but also to comfort, convenience and entertainment features (for instance, air conditioning, seat heating, video systems). The advent of new technologies such as X-by-wire is putting additional demand on the battery. Effective vehicular electric power management helps to enhance fuel economy, battery life, vehicle safety, availability, and maintainability (Bin, Li, & Feng, 2009; Cox & Bertness, 2002; Cugnet & Sabatier, 2009; Meissner & Richter, 2005; Schollmann, Rosenmayr, & Olk, 2005; Scacchioli, Pisu, & Rizzoni, 2007; Serrao, Onori, Rizzoni, & Guezennec, 2009).

Accurate and reliable knowledge of the battery state is crucial to achieve these goals. The battery state consists of state-of-charge (SOC) and state-of-health (SOH). The SOC represents the stored power and energy available, and the SOH is an indication of cranking power capability and battery capacity. A primary

functionality of automotive starting, lighting, and ignition (SLI) batteries is to deliver high power in short periods (for instance, to crank an engine), and the battery capacity indicates its energy storage capability. This paper focuses on SLI battery SOH monitoring based on its cranking power capability.

A key challenge of on-board battery SOH monitoring is the *robustness* requirement. Various types of aftermarket batteries are available for the same vehicle platform. Since there is no control over the type of battery which the vehicle owner may choose, a reliable on-board battery SOH monitoring method has to be robust with respect to the variation of the battery types. A well-known approach to battery SOH monitoring is based on battery resistance/impedance (Blanke, Bohlen, & Buller, 2005; Cox & Bertness, 2002; Huet, 1998; Meissner & Richter, 2001). Although SOH information inferred from battery resistance/impedance measurement is valuable, experimental results have shown significant variations of battery resistance/impedance among different battery types. Because of the cost and complexity of on-board implementations it is not feasible to use a battery identification algorithm combined with a calibration table for each possible battery type. Therefore, in order to achieve accurate and robust battery diagnosis/prognosis, the battery resistance needs to be combined with other features via an integrated algorithm (Blanke et al., 2005; Meissner & Richter, 2001).

In the fault diagnosis literature, there has been significant research activity in the design and analysis of model-based diagnostic schemes (see, for instance, Blanke, Kinnaert, Lunze, & Staroswiecki, 2006; Chen & Patton, 1999; Ding, 2008; Gertler, 1998; Isermann, 2006; and the references cited therein), including

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parity relations, observer-based methods, and parameter identification techniques. This paper presents a parity-relation-based method for robust SOH monitoring for lead acid batteries to ensure engine cranking capability. Specifically, the paper has two main contributions. First, a new battery model describing the battery dynamics during engine cranking is presented. Through analysis of extensive real vehicle cranking data, battery *ohmic behavior* and *voltage loss* have been clearly observed during engine cranking. The new battery model, which takes into account both the battery's voltage loss and ohmic behaviors during cranking, is more accurate and computationally efficient than conventional models. This is very important for real-time on-board implementation of battery SOH monitoring algorithms. Second, a parity-relation-based integrated battery SOH monitoring method is developed. Based on extensive battery testing results, it is found that, in addition to resistance, battery voltage loss during engine cranking also provides valuable information of battery SOH. A parity relation is designed to characterize the behaviors of good batteries during engine cranking. A residual, defined as the discrepancy between the actual battery voltage measurement and its estimate generated by the calibrated parity relation, is used to infer battery SOH. Analytical results indicate that the designed residual combines the SOH information provided by both battery resistance and voltage loss, hence achieving better fault diagnostic performance.

This paper is organized as follows. Section 2 describes the new battery model during engine cranking. Section 3 briefly reviews a conventional resistance-based battery SOH monitoring approach, and Section 4 presents the parity-relation-based SOH monitoring method. The calibration and on-board implementation of the presented algorithm are described in Section 5. Section 6 shows several representative examples of algorithm performance evaluation results using real vehicle cranking data. Finally, Section 7 gives some concluding remarks.

2. Battery model during engine cranking

A good understanding of the battery dynamics is essential for the development of effective SOH monitoring algorithms. In this section, the battery dynamics during engine cranking is investigated.

A widely used equivalent circuit model describing battery dynamics during normal driving operations is the Thevenin model shown in Fig. 1, (see, for instance, Blanke et al., 2005; Emadi et al., 2004; Huet, 1998), where R_b is the ohmic resistance, V_{ocv} is the battery open circuit voltage (OCV), C_{dl} is the double layer capacitor, and R_{CT} is the charge transfer resistance. More sophisticated models have also been introduced, by including additional components such as the Warburg impedance (Buller, Thele, Karden, & De Doncker, 2003), constant phase

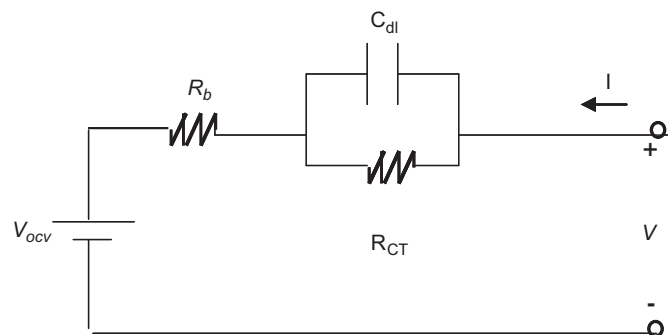


Fig. 1. Thevenin battery model.

elements (Nelatury & Singh, 2002), or another RC component representing the diffusion process (Verbrugge, Frisch, & Koch, 2005).

During normal driving operations, the alternator is the primary energy source, and the battery, as the secondary energy source, supplies electric power to the vehicle under the following conditions:

- the energy generated by the alternator cannot meet the demanded load current (for instance, when the internal combustion engine is on idle with many electrical consumers being switched on, or the alternator is defective or off);
- the battery stabilizes the system voltage in the presence of sudden electrical load changes.

As a result, the battery's discharging current during normal driving operations is much smaller than during engine cranking. In the former case, the battery current is often less than 50 A, and it can possibly reach 1000 A during engine cranking, depending on the specific configuration of the starting system. Therefore, the battery's dynamics during engine cranking can be very different from that of normal driving operations. In this research, the battery's dynamics during engine cranking is investigated, as detailed in the following sections.

2.1. Battery ohmic behavior during engine cranking

Typical battery voltage and current signals during vehicle starting are shown in Fig. 2. When the circuit between the battery and starter is completed by the starter solenoid, there is a large inrush current, which corresponds to the large initial battery voltage drop shown in Fig. 2. The subsequent wave-like variations in battery voltage and current signals are generated by engine compression and expansion cycles. The engine starts after it reaches a particular speed (e.g., 500 rpm).

The portion of battery signals corresponding to the short period of engine cranking shown in Fig. 2 is extracted and re-plotted in a $V-I$ plot shown in Fig. 3 (A linear least squares fit line is also shown). An ohmic relationship between the battery voltage and current can be clearly seen, which justifies the simplified ohmic model shown in Fig. 4. Therefore, the extra double layer RC components in the Thevenin model (Fig. 1) or other more

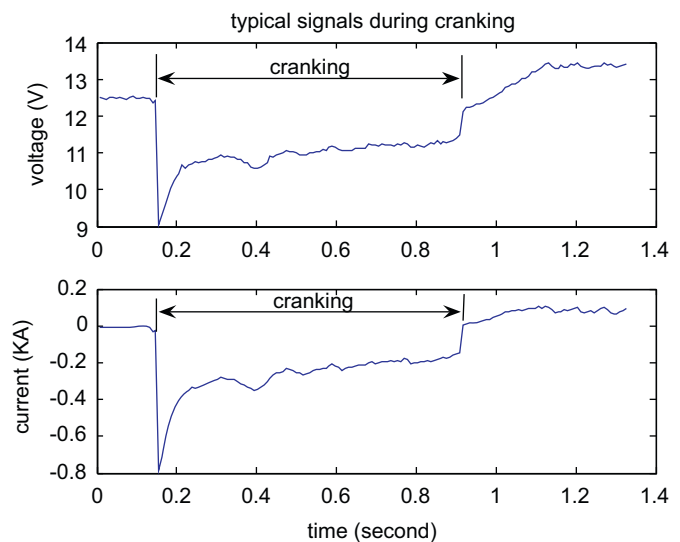


Fig. 2. Typical battery voltage (volts) and current (KA) signals during vehicle starting.

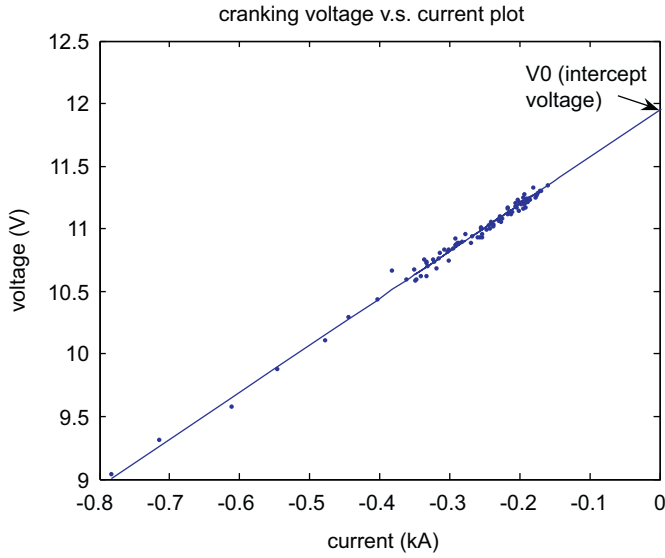


Fig. 3. Extracted signal in a V – I plot (a linear least squares fit line is also shown).

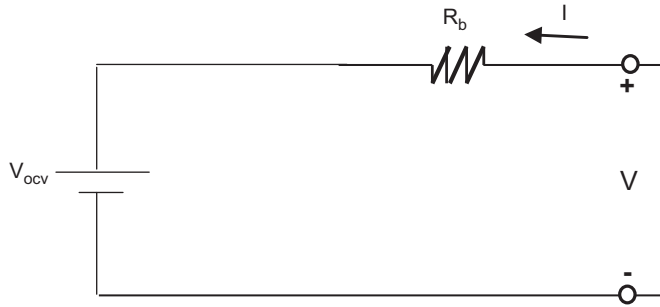


Fig. 4. Battery ohmic model.

complicated components, such as the Warburg impedance and constant phase elements, are not needed to model the battery dynamics during the engine cranking period. Hence, the resulting battery model is more computationally efficient than conventional models, which is important to on-board real-time applications.

2.2. Battery voltage loss during cranking

In the battery ohmic model shown in Fig. 4, the battery current $I(t)$ and voltage $V(t)$ satisfies

$$V(t) = V_{ocv} + I(t)R_b \quad (1)$$

where $I(t) < 0$ represents discharging current during engine cranking. Based on Eq. (1), the intercept voltage V_o (i.e., the voltage corresponding to $I=0$), as shown in Fig. 3, should be equivalent to the open circuit voltage V_{ocv} . However, analysis of various real vehicle cranking data has indicated that the intercept voltage V_o is always lower than V_{ocv} , which is due to a battery voltage loss during cranking.

The value of voltage loss can be estimated as follows. A linear regression in the form of

$$V(t) = V_o + I(t)R_b \quad (I(t) < 0 \text{ for discharge}) \quad (2)$$

can be applied to estimate the intercept voltage V_o and the battery resistance R_b by using the measured battery current $I(t)$ and voltage $V(t)$. After V_o is obtained, the battery voltage loss is

given by

$$V_{loss} = V_{ocv} - V_o, \quad (3)$$

where V_{ocv} is the open circuit voltage measured when the vehicle is off. For instance, for the specific example shown in Fig. 3, the measured battery open circuit voltage before cranking is 12.60 V, while the estimated intercept voltage V_o is about 11.95 V. Therefore, the voltage loss is 0.65 V.

2.3. New battery model during engine cranking

Based on the above discussions the new battery model shown in Fig. 5 is proposed, where R_b is the battery ohmic resistance, and V_{loss} represents the voltage loss during engine cranking. Therefore, the battery voltage $V(t)$ and current $I(t)$ (note that $I(t) < 0$ for discharge) satisfies

$$V(t) = V_{ocv} - V_{loss} + I(t)R_b. \quad (4)$$

Compared with conventional battery models, the new model takes into account both the ohmic behavior and voltage loss of the battery during engine cranking, therefore, it is a more accurate and computationally efficient representation of battery dynamics during engine cranking.

3. Conventional resistance-based battery SOH monitoring method

The well-known conventional approach to battery SOH monitoring is based on battery resistance using the Ohm's law (Berndt, 2003). The variables used to calculate the battery resistance during engine cranking are illustrated in Fig. 6. Specifically, ΔV is the voltage difference between V_1 (i.e., the minimum voltage recorded at the instant of starter engagement) and V_0 (i.e., the voltage just prior to starter engagement). The current change ΔI is the difference between I_1 (i.e., the maximum discharging current corresponding to V_1 at the instant of starter engagement) and I_0 (i.e., the current corresponding to V_0 recorded just prior to starter engagement). Then, the battery cranking resistance is calculated as (Berndt, 2003)

$$R = \frac{\Delta V}{\Delta I} = \frac{V_1 - V_0}{I_1 - I_0}. \quad (5)$$

The SOH information provided by battery resistance is valuable. However, experimental results have indicated that resistance-based SOH monitoring method is not robust to variation of battery types, which can potentially result in mistaken replacement of good batteries or missed detections leading to cranking failures and customer dissatisfactions. More discussion of this conventional method and some comparative studies will be given in Section 6.

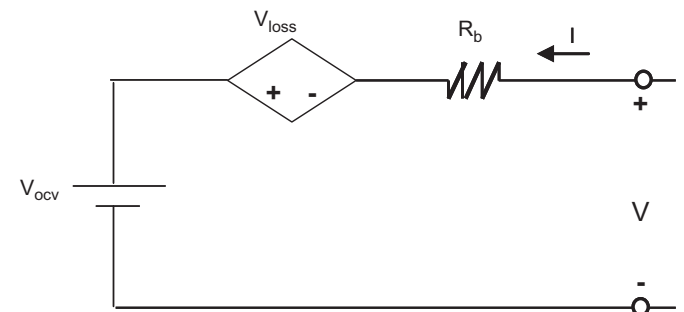


Fig. 5. New battery model during cranking.

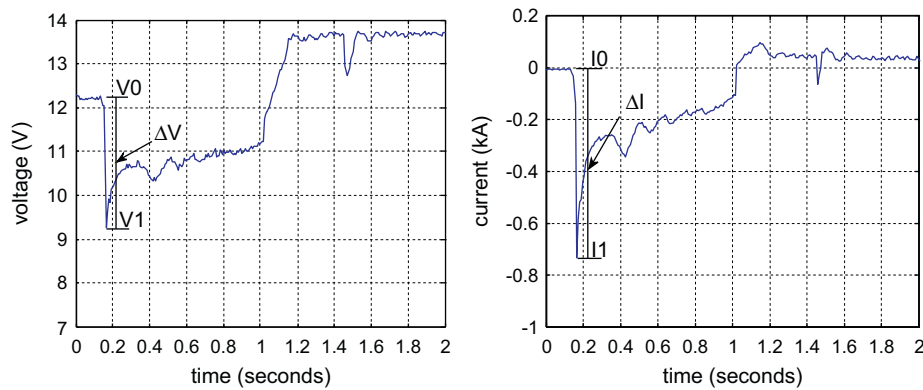


Fig. 6. Voltage (volts) and current (kA) plots illustrating the calculation of battery cranking resistance.

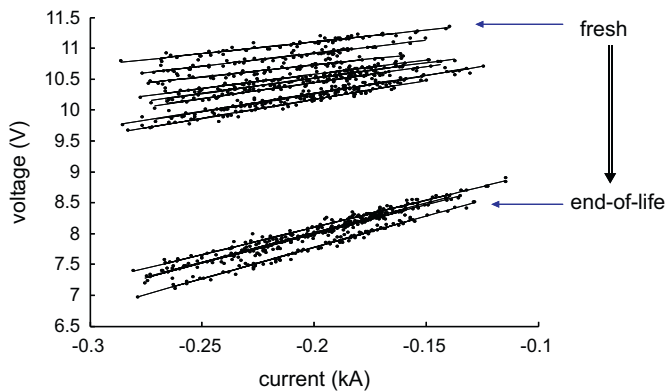


Fig. 7. V-I plot of cranking data collected periodically during a complete accelerated aging cycling process of a battery (the linear least squares fit line for each crank data set is also shown).

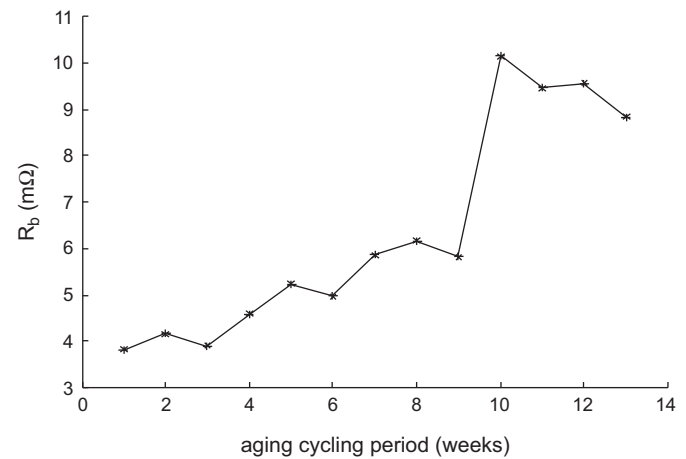


Fig. 8. Change of battery resistance R_b in a complete accelerated aging cycling process.

4. Parity-relation-based battery SOH monitoring method

4.1. Battery SOH indicators

It is well-known that battery resistance increases as a result of battery aging (see, for instance, Huet, 1998). However, to provide robust battery diagnosis, methods based on battery resistance alone are not reliable enough, and an integrated algorithm is needed (Blanke et al., 2005; Meissner & Richter, 2001). In this research work, through extensive battery testing and analysis of real vehicle cranking data, it is found that, in addition to battery resistance, voltage loss during engine cranking is also a good indicator of battery SOH, which can be used to enhance battery diagnostics and prognostics.

As an illustrative example, Fig. 7 shows a few sets of cranking data collected periodically during a complete aging process of a battery, which was aged from fresh to dead by following an SAE battery aging cycling procedure. To minimize the effect of battery SOC and temperature variations, the battery was always conditioned to a high SOC level of about 95% and 25 °C when vehicle cranking tests were conducted. As shown in Fig. 3, there is a linear relationship between battery voltage and current during engine cranking, and most of the samples correspond to a current in the range of -300 to -100 A. Therefore, without loss of generality, only the data samples with battery current in the range of -300 to -100 A are plotted in Fig. 7. For the data samples corresponding to each crank, the linear least squares fit line is also shown.

As can be seen from Fig. 7, as the battery is aged, not only the battery resistance (i.e., the slope of the linear regression fit line) increases, but also the intercept voltage drops, which indicates increasing battery voltage loss. Based on Eqs. (1) and (3), the parameters of battery resistance, R_b , and voltage loss, V_{loss} , corresponding to each set of cranking data given in Fig. 7 are extracted using linear regression techniques. The results are shown in Figs. 8 and 9. As can be seen, both battery resistance and voltage loss have a general trend of increasing during an aging process, indicating the degradation of battery SOH. Therefore, these two SOH indicators can possibly be integrated to enhance the performance of battery diagnostics/prognostics, which motivate the battery SOH monitoring method presented in the subsequent sections.

Remark 1. It is worth noting that the sudden jump from weeks 9 to 10 is the accumulated result of gradual degradation during cycling. For instance, prolonged cycling could cause the active material to be so porous that the contact between the positive active material and the grid will eventually get lost at a certain point. Additionally, it could also result from the loss of a cell.

4.2. Overview of battery SOH monitoring method

Fig. 10 illustrates a schematic diagram of the presented parity-relation-based on-board battery SOH monitoring method. It consists of the following four components: (1) *signal pre-processing*: the battery voltage and current signals during

vehicle starting are pre-processed to extract the portion of signals corresponding to the short period of engine cranking. (2) *Voltage estimation*: a calibrated parity relation model, characterizing the dynamics of good batteries during engine cranking, is used to generate an estimate of the battery voltage corresponding to a given battery current signal. (3) *Residual generation*: the residual is defined as the discrepancy between an actual voltage measurement and its estimate provided by the parity relation model. (4) *Residual evaluation*: by comparing the diagnostic residual with a pre-defined threshold, the battery SOH can be inferred. Additionally, the effects of battery SOC and temperature are taken into account during the calibration and residual evaluation procedures. More details on an algorithm calibration and an on-board implementation are given in Section 5.

Fault sensitivity and robustness with respect to modeling uncertainty are two important performance metrics of fault diagnostics. In general, the sensitivity and robustness properties can be enhanced during residual generation and/or during residual evaluation (Chen and Patton, 1999). In this research work, the first approach is employed. Specifically, the residual signal is designed to combine the two SOH indicators discussed above, including battery resistance and voltage loss during engine cranking, hence enhancing diagnostic performance. The residual generation method is detailed below.

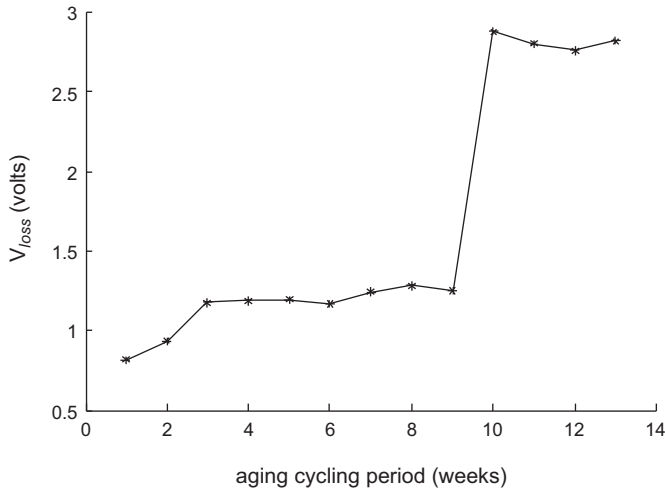


Fig. 9. Change of battery voltage loss V_{loss} in a complete accelerated aging cycling process.

4.3. Residual generation and evaluation

4.3.1. Residual generation

As shown in Fig. 10, the diagnostic residual is defined as the discrepancy between the actual battery voltage and its estimate provided by a calibrated parity relation model representing dynamics of good batteries. Intuitively, the residual represents the deviation between the behavior of the battery under testing and that of good batteries. Specifically, by denoting the voltage and current of the battery under testing as $V(t)$ and $I(t)$, respectively, the residual $r(t)$ is given by

$$r(t) = V(t) - \hat{V}(t) \quad (6)$$

where $\hat{V}(t)$ is the estimated voltage generated by using

$$\hat{V}(t) = \bar{V}_0 + I(t)\bar{R}_b, \quad (7)$$

where $\bar{V}_0$ and $\bar{R}_b$ are parameters of the parity relation calibrated by utilizing cranking data collected from good batteries (see Section 5 for more details on the calibration procedure).

4.3.2. Residual evaluation

A unique feature of the residual $r(t)$ given by Eq. (6) is its capability of combining the battery SOH information provided by battery resistance as well as voltage loss. The following analysis gives a better insight into this important feature of residual $r(t)$. By using Eq. (4), the measured battery voltage $V(t)$ satisfies

$$V(t) = V_{ocv} - V_{loss} + I(t)R_b, \quad (8)$$

where V_{ocv} , V_{loss} , and R_b are the open circuit voltage, voltage loss, and ohmic resistance of the battery under testing, respectively. By substituting Eqs. (7) and (8) into Eq. (6), the following equation is obtained

$$r(t) = V_{ocv} - \bar{V}_0 - V_{loss} - I(t)(\bar{R}_b - R_b). \quad (9)$$

Besides, from Eq. (3), the following equation can be obtained

$$\bar{V}_0 = \bar{V}_{ocv} - \bar{V}_{loss}. \quad (10)$$

By using Eq. (10), Eq. (9) can be rewritten as

$$r(t) = (V_{ocv} - \bar{V}_{ocv}) + (\bar{V}_{loss} - V_{loss}) - I(t)(\bar{R}_b - R_b). \quad (11)$$

Since the open circuit measurement satisfies $V_{ocv} \approx \bar{V}_{ocv}$ at the same battery SOC and temperature, the above equation can be further simplified as

$$r(t) \approx (\bar{V}_{loss} - V_{loss}) - I(t)(\bar{R}_b - R_b) \quad (12)$$

As shown in Figs. 8 and 9, both the battery voltage loss, V_{loss} , and ohmic resistance, R_b , increase as a result of battery aging.

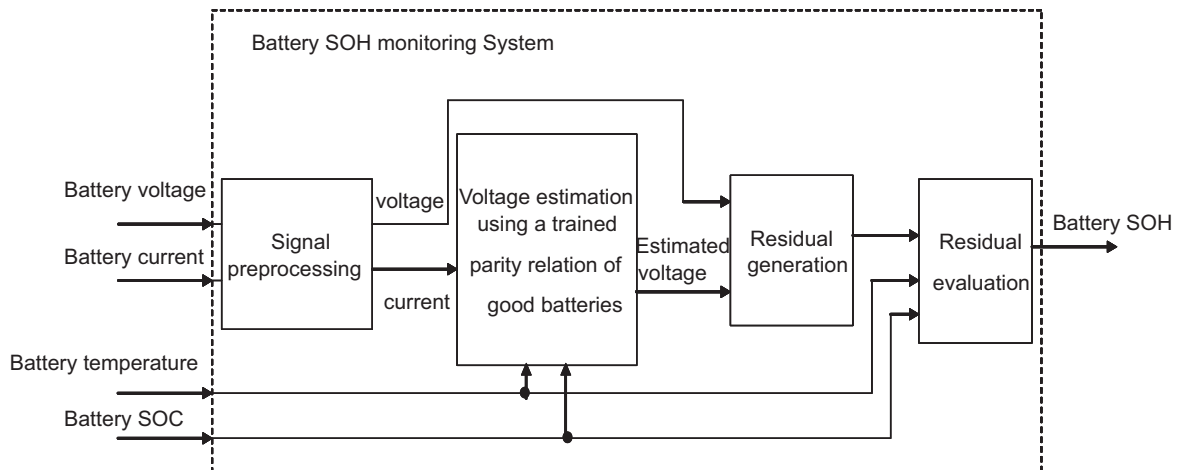


Fig. 10. Parity-relation-based battery SOH monitoring method.

Therefore, the residual $r(t)$ given by Eq. (12) combines the changes in both battery voltage loss and internal resistance (note that $I(t) < 0$ represents the discharging current during engine cranking). More specifically, the residual should remain positive or near zero for good batteries since $V_{loss} \approx \bar{V}_{loss}$ and $R_b \approx \bar{R}_b$, and will become significantly negative when V_{loss} and/or R_b increase as a result of battery aging. Therefore, the residual $r(t)$ offers better diagnostic performance than conventional methods that are solely based on battery resistance, since it takes into account the SOH information provided by both battery resistance and voltage loss during an engine cranking.

It is worth noting that, in the fault diagnosis literature, the residual is often designed to remain around zero under normal conditions and to take significantly non-zero values in the presence of a fault. That is a little different from the residual defined in the presented method. Specifically, based on the residual $r(t)$ designed above, positive or zero values of the residual (i.e., the cranking voltage is higher than an average good battery) represent high SOH, and significantly negative residual values (i.e., low cranking voltage) represent low SOH.

5. Calibration and implementation of the battery SOH monitoring method

In this section, the procedures for off-line calibration and on-board implementation of the battery SOH monitoring algorithm are described.

5.1. Off-line calibration of parity relation model

An off-line calibration procedure is used to obtain a parity relation model, characterizing the dynamics of good batteries during an engine cranking at different SOC levels (e.g., 100%, 75%, 50%, 25%) and temperatures (e.g., 50, 25, 0, -18°C). Specifically, to determine the calibration parameters $\bar{V}_0$ and $\bar{R}_b$ in Eq. (7), the following procedure is adopted:

- 1) Select a few batteries with high SOH (e.g., fresh batteries) and condition them to a specific SOC level and temperature under consideration.
- 2) Conduct cranking tests and obtain the battery cranking voltage $V(t)$ and current $I(t)$ signals for each crank.
- 3) Use all the crank data collected at step 2 to perform a linear regression in the form of

$$V(t) = \bar{V}_0 + I(t)\bar{R}_b \quad (13)$$

where $\bar{V}_0$ is the intercept voltage, and $\bar{R}_b$ is the slope of the linear regression line (see Fig. 11 for an illustrative example). Record the battery parameters $\bar{V}_0$ and $\bar{R}_b$.

- 4) Repeat the above steps at different battery SOC levels (e.g., 100%, 75%, 50%, 25%) and temperatures (e.g., 50, 25, 0, -18°C).

The parity relation parameters obtained from the above off-line calibration procedure are then stored in a calibration table for on-board vehicle applications. Specifically, given a current signal, appropriate values of $\bar{V}_0$ and $\bar{R}_b$ can be obtained from the calibration table based on the SOC and temperature of the battery under testing. Then, a voltage estimate is generated by using Eq. (7) and compared with the actual voltage measurement for residual generation.

5.2. Calibration of residual threshold

To determine the battery's cranking capability, the generated residual is compared to a pre-designed threshold. It is noted that a

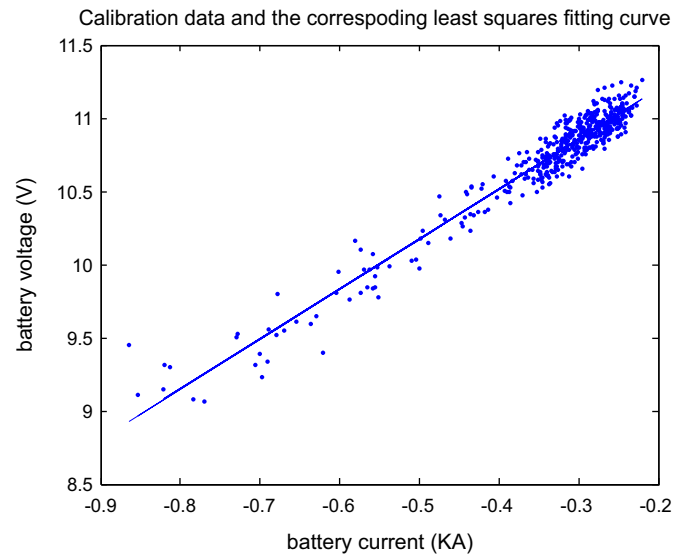


Fig. 11. Example of battery voltage and current signals for parity relation calibration.

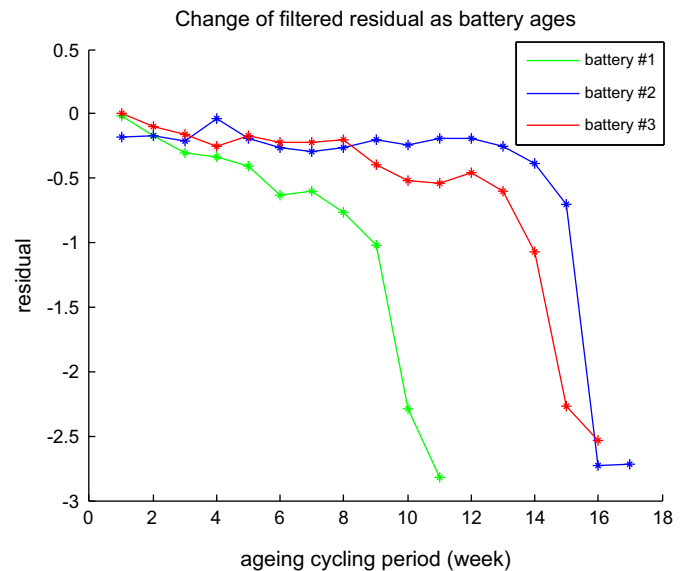


Fig. 12. Changes of residuals for three batteries aged from fresh to cranking failure.

negative threshold should be used based on the residual generation procedure described in Section 4.3. Therefore, a high threshold will lead to unnecessary replacement of batteries with reasonably high SOH and extra warranty cost to the OEMs, and a low threshold will result in missed pre-warning of pending cranking failure and customer dissatisfactions.

To minimize the effect of disturbance and sensor noise, the residual signal $r(t)$ is filtered by a low-pass filter before it is compared with the threshold. In this research, as a simple filtering method, the average of the residual signal corresponding to each crank is computed. The threshold on an averaged residual is calibrated based on the analysis of extensive battery cranking data collected from 30 batteries and 2 vehicles. Moreover since the battery's available cranking power changes with respect to temperature, the residual threshold is calibrated as a function of battery temperature (e.g., 50, 25, 0, -18°C).

As an illustrative example, Fig. 12 shows the change of filtered residuals corresponding to three batteries that were aged starting from fresh until the batteries failed to crank the vehicle by using

an SAE battery aging procedure. Specifically, the residuals are generated based on cranking data at 25 °C and approximately 95% battery SOC periodically collected during an aging cycling process. Each point shown in Fig. 12 represents the averaged residual value corresponding to a specific crank using one of the three batteries. As can be seen, a residual threshold of -1.2 may be chosen, so that a timely pre-warning of low battery SOH can be given to avoid cranking failures.

Remark 2. It is worth noting that the residual threshold given above is chosen based on observations. A more systematic method is to test a large number of battery samples with different SOH and study the statistical behaviors of the residual. Then, an appropriate statistical detection method (for instance, CUSUM or GLR test) can be utilized to systematically design the threshold (Blanke et al., 2006).

5.3. On-board implementation of the battery SOH monitoring algorithm

This section describes the on-board implementation procedure of the presented battery SOH monitoring algorithm. The inputs to the algorithm are battery cranking voltage and current, battery start-up SOC, and battery temperature.

It is worth noting that low battery cranking power can be caused by low battery SOH and/or low SOC. To determine if a battery should be replaced or recharged to ensure the vehicle's start-up ability, the following method is adopted. If the residual is below its threshold, and the battery SOC is above a certain threshold (calibrated based on requirements of GM's regulated voltage control algorithms for electric power management), then the battery should be replaced. Otherwise, the battery should be recharged first, because in this case the low cranking power might be due to low SOC.

The main component of the on-board computational procedure of the battery SOH monitoring algorithm is as follows.

- 1) obtain the battery start-up SOC and temperature;
- 2) based on battery start-up SOC and temperature, obtain parity relation parameters $\bar{V}_0$ and $\bar{R}_b$ from the calibration tables;
- 3) obtain battery cranking voltage $V(t)$ and current $I(t)$;
- 4) for each sample of battery current $I(t)$, compute its voltage estimate $\hat{V}(t)$ by using Eq. (7);
- 5) compute the diagnostic residual signal $r(t)$ using Eq. (6), and take the average of it to obtain r_{avg} ;
- 6) based on battery SOC and temperature, obtain a residual threshold $\bar{r}$ and an SOC threshold from the corresponding calibration tables.
- 7) If $r_{avg} < \bar{r}$ and
 - a. the start-up SOC is above the SOC threshold, issue a message of "Replace Battery," return;
 - b. the start-up SOC is below the SOC threshold, issue a message of "Recharge Battery," return.

It is worth noting that, to determine a recharging or replacement decision, a possible alternative approach is to calibrate the residual threshold $\bar{r}$ as a function of battery SOC as well. However, this will add another dimension to the calibration table of $\bar{r}$, leading to extra implementation cost and complexity. Therefore, that approach is not adopted in this research.

6. Algorithm performance evaluation

The effectiveness of the algorithm has been extensively verified using vehicle cranking data collected from 30 batteries tested at

various battery SOC levels and four different temperatures of 50, 25, 0, and -18 °C. Among the 30 batteries, the first set of 10 batteries were fresh batteries aged by following an SAE aging cycling procedure, the second set of 10 batteries were fresh batteries aged by using an aging cycling procedure provided by a battery supplier, and the third set of 10 batteries were field batteries with different service ages collected from dealer service garages.

To illustrate the effectiveness of the battery SOH monitoring method, several representative examples at 25 °C are given below. The calibration values for SOC threshold and residual threshold at 25 °C are 60% and -1.2 V, respectively.

6.1. Evaluation results of field batteries

For the 10 selected field batteries acquired from dealer service garages, the following battery test procedure was used. Each battery was first fully charged. Then, its SOC was gradually reduced until it reaches 0% SOC, or it failed to crank the vehicle. Note that the battery's SOC was controlled based on its measured actual capacity, and at each SOC level the battery was allowed to rest for at least 8 h before an open circuit measurement and vehicle cranking test were conducted. At each condition, three vehicle cranks were carried out.

As an example, Table 1 gives the results for battery #69 cranked three times at each of the four SOC levels: 100%, 90%, 80%, and 75%. The battery failed to crank the vehicle at the 3rd crank of 75% SOC and at the next SOC level below 75%. The residual value corresponding to each crank is included. Focusing on the data that is shown in Table 1, the algorithm determines that cranks 2 and 3 at the 100% SOC level and all cranks thereafter have a residual value below the threshold of -1.2 . Moreover, the corresponding SOC of each of these cranks is higher than the 60% threshold. This would warrant a message of "Replace Battery". This message is consistent with the message of "Replace Battery" issued by the off-line Midtronics battery tester Micro500XL, whose cost is much more expensive than the proposed on-board battery SOH monitoring method.

Table 2 reports another example, i.e., the results of battery #33 tested at 25 °C. The battery failed to crank the vehicle at the next SOC level below 40% SOC. As illustrated in the table, at the 40% SOC level (below the SOC threshold of 60%), residual values are below the threshold of -1.2 . Hence, the algorithm issues the message "Recharge Battery". The Midtronics battery tester Micro500XL issues "Good" or "Good-Recharge" at SOC levels at and above 50% SOC, and "Replace Battery" at 45% SOC and 40% SOC, which could result in mistaken replacement of a battery with reasonably good SOH. Hence, the proposed algorithm gives a more reliable decision than the Midtronics battery tester, which employs a resistance-based SOH monitoring method.

6.2. Comparison with conventional resistance-based battery SOH monitoring method

As described in Section 3, a well-known conventional approach to battery SOH monitoring is based on its internal resistance. In contrast, the presented parity-relation-based method combines the SOH information provided by both battery resistance and

Table 1
Battery #69 at 25 °C.

SOC crank#	100% SOC	90% SOC	80% SOC	75% SOC
1	-1.136	-1.518	-2.055	-2.532
2	-1.231	-1.723	-2.351	-3.110
3	-1.283	-1.858	-2.414	failure

Table 2
Battery #33 at 25 °C.

SOC crank#	100% SOC	90% SOC	80% SOC	75% SOC	70% SOC	
1	0.186	0.144	0.025	−0.055	−0.100	
2	0.310	0.163	0.014	−0.071	−0.100	
3	0.278	0.180	0.017	−0.062	−0.088	
SOC crank#	65% SOC	60% SOC	55% SOC	50% SOC	45% SOC	40% SOC
1	−0.094	−0.149	−0.185	−0.356	−0.416	−1.690
2	−0.095	−0.119	−0.201	−0.380	−0.468	−1.411
3	−0.061	−0.092	−0.176	−0.358	−0.467	−1.203

Table 3
Battery JCI006 at high SOC and 25 °C (battery cranking resistance R_b (mΩ) and residual r_{avg}).

Crank#	Test period 1		Test period 2		Test period 3		Test period 4	
	R_b	Residual	R_b	Residual	R_b	Residual	R_b	Residual
1	3.240	0.200	3.518	0.075	3.687	0.052	3.649	0.007
2	3.338	0.206	3.231	0.115	3.644	0.095	3.950	0.009
3	3.356	0.217	3.529	0.145	3.671	0.126	3.949	0.026
Crank#	Test period 5		Test period 6		Test period 7		Test period 8	
	R_b	Residual	R_b	Residual	R_b	Residual	R_b	Residual
1	3.906	−0.018	3.991	−0.072	3.995	−0.087	4.097	−0.156
2	3.676	0.056	4.075	0.008	3.986	−0.009	4.393	−0.140
3	3.925	0.052	4.007	0.002	3.921	−0.001	4.341	−0.130
Crank#	Test period 9		Test period 10		Test period 11		Test period 12	
	R_b	Residual	R_b	Residual	R_b	Residual	R_b	Residual
1	3.841	0.031	4.107	0.012	4.864	−0.266	4.768	−1.433
2	3.647	0.027	3.921	0.067	4.886	−0.152	4.997	−1.628
3	3.891	0.026	4.073	0.069	4.653	−0.135	5.362	−1.871

Table 4
Battery #1–#10 at first week (battery cranking resistance R_b and residual r_{avg}).

Battery#	R_b	Residual
1	7.010	0.114
2	6.881	0.142
3	6.918	0.109
4	6.847	0.112
5	6.902	0.137
6	6.615	0.463
7	6.534	0.486
8	6.481	0.473
9	6.639	0.470
10	6.548	0.453

voltage loss, hence improving fault sensitivity and robustness. This advantage is illustrated by the following examples.

In this battery test, 10 batteries of similar types were aged from fresh to cranking failure by using an SAE aging cycling procedure. At the end of each week of the overall aging cycling process, the batteries were conditioned to an SOC level of approximately 95% SOC and 25 °C, and three vehicle cranks were conducted. As an example, Table 3 shows the results of the calculated battery cranking resistance (see Section 3) and residual values for battery JCI006. The battery failed to crank the vehicle at test period 14 (week 14). From Table 3, for the conventional resistance-based SOH monitoring method, a resistance threshold

of about 4.9 mΩ should be chosen to provide a pre-warning of pending cranking failure at test period 14. However, due to variation of battery types, it is very difficult to calibrate a resistance threshold that is good for different battery types, as illustrated by the next example.

Table 4 shows the battery cranking resistance (see Section 3) and residual values for another set of 10 batteries of similar types, calculated when the batteries were fresh. Similarly, these fresh batteries were cranked at approximately 95% SOC and 25 °C. As can be seen in Table 4, these fresh batteries have an average resistance of about 6.8 mΩ. As in the example of battery JCI006 shown in Table 3, if only resistance is used to determine battery SOH with a threshold of 4.9 mΩ, all these fresh batteries will be mistakenly determined as batteries of low SOH and be replaced. However, the residuals of these fresh batteries all take small positive values, indicating good battery SOH. Hence, the proposed method is more robust to variation of battery types than the conventional resistance-based method, which is crucial to on-board automotive battery SOH monitoring applications, since there is no control over the type of aftermarket batteries the vehicle owner may use.

7. Conclusions

A parity-relation-based integrated SOH monitoring method for lead acid batteries is presented in this paper. This method combines the SOH information provided by both battery resis-

tance and voltage loss during engine cranking, hence achieving better diagnostic performance than conventional resistance-based methods. The algorithm provides a timely pre-warning of pending vehicle cranking failure and helps to reduce battery related no-trouble-found cases and OEM warranty costs. Extensive evaluation results using real vehicle cranking data have shown the effectiveness of the proposed method.

As discussed in Section 5, the investigation of a statistical detection method is a very interesting topic for future research. Another topic for future research work is to extend the presented method by considering advanced battery SOH prognosis. Therefore, a meter indicating battery remaining useful life can be offered. In addition, an extension of the method to other battery types (for instance, Nickel Metal Hydride batteries and Li-Ion batteries) is very important for hybrid electric vehicle applications (see, for instance, Bin et al., 2009; Tang, Zhang, Koch, & Frisch, 2008; Hu, Yurkovich, Guezennec, & Yurkovich, 2009).

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